PATENT PROTECTION, MARKET UNCERTAINTY, AND R&D INVESTMENT

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Abstract—The main reason governments grant patent protection is to spur innovation. However, the size of the R&D stimulus from patent protection is far from clear because it depends on how effective patents are as a mechanism for appropriating returns. Drawing on real options investment theory, this paper highlights one mechanism through which patents may improve appropriability and stimulate R&D investment: patents reduce the effect of market uncertainty on the firm's investment decision. We find that firm-level R&D investment falls in response to higher levels of uncertainty, but that patent protection partially mitigates the influence of uncertainty.

I. Introduction

THE main reason governments grant patent protection is to spur innovation. Patents give inventors temporary monopoly rights that allow them to appropriate a greater share of the returns from their innovations, and this augments private incentives to undertake research and development (R&D) investment. Consequently, patent protection should stimulate private R&D investment. However, the size of the R&D stimulus from patent protection is far from clear because it depends on how effective patents are as a mechanism for appropriating returns.

Drawing on real options investment theory, this paper highlights one mechanism through which patents may improve appropriability and stimulate R&D investment: patents reduce the effect of market uncertainty on the firm's investment decision. The real options framework predicts that greater uncertainty about market revenues may reduce current investment in irreversible capital by increasing the value of waiting to invest (Pindyck, 1991; Dixit, 1992; Dixit & Pindyck, 1994). R&D investment is highlighted in this literature as a particularly relevant example of irreversible capital because a large proportion of R&D supports the salaries of research personnel and cannot be recouped if projects fail. Firms can avoid large losses by waiting for new information about market conditions and forgoing investment when information is unfavorable. This would lower current R&D investment. Alternatively, a patent may protect the firm from market competition due to, among other things, imitation by rivals. This reduces the patenting firm's perceived level of market uncertainty, decreases the value of waiting, and leads to greater current R&D investment.

In this paper, we undertake an empirical analysis to investigate the evidence supporting the real options investment theory and the interaction between uncertainty and patent protection for firm-level R&D investment. Specifically, we examine two questions. First, do firms reduce current R&D investment in response to higher perceived levels of market uncertainty? Second, does patent protection mitigate the firm's R&D investment response to market uncertainty? If patent protection mitigates market uncertainty, R&D investment by patenting firms should be less responsive to revenue uncertainty. Our regression analysis examines these hypotheses using panel data on innovative firms in Germany's manufacturing sector.

We find that firm-level R&D investment falls in response to higher levels of uncertainty as perceived through revenue volatility. Consistent with the orientation of R&D investment toward innovation, it is revenue volatility in the firm's new product markets that reduces R&D investment and not revenue volatility in the firm's established product markets. Moreover, we find that patent protection mitigates the influence of uncertainty on the firm's R&D decision. This mitigating effect, however, is contingent on patenting being an effective means of market protection. As one would expect, patent protection does not mitigate the effect of uncertainty in industries where patents are ineffective. Our models control for access to internal and external capital, nondiversifiable risk, and a variety of other potential determinants of R&D investment. The panel data models account for firm-specific effects that may influence investment such as firm-level risk aversion or unobserved heterogeneity in managerial practices. We also check the robustness of our results using instrumental variables methods and alternative model specifications.

The next section of the paper provides a brief review of the prior literature on the investment-uncertainty relationship. Section III discusses the data, our measure of uncertainty, and other covariates. Our econometric approach, regression results, and robustness checks are presented in section IV, and concluding remarks are given in section V.

II. Literature and Hypotheses

The relationship between investment and uncertainty is an important ongoing topic of research in both the theoretical and empirical literatures. In the theoretical literature, Abel et al. (1996) show that investment decisions involve the acquisition or exercise of reversibility and expandability options. The reversibility option captures the value of opportunities and costs associated with disinvestment at some point in the future. This option increases the incentive for current investment when future returns are uncertain because firms acquire this option by purchasing capital. The

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expandability option captures the value of opportunities and costs associated with investment at some point in the future. This option decreases the incentive for current investment when future returns are uncertain because firms acquire this option by delaying the purchase of capital. Since these options have offsetting effects on the incentive to invest, their model shows that the net effect of uncertainty on current investment is theoretically ambiguous (for reviews of the theoretical and empirical literatures emphasizing physical capital investment, see Butzen & Fuss, 2002; Carruth, Dickerson, & Henley, 2000; Lensink, Bo, & Sterken, 2001).

The type of the capital investment will partly determine the nature of the options facing the firm. For instance, research and development is typically considered in the literature as an investment that has no (or extremely small) reversibility option, but has a significant expandability option. R&D investment is often characterized as completely irreversible (see, for instance, Dixit & Pindyck, 1994) since these expenditures are directed toward the salaries of research personnel and the purchase of task-specific equipment and materials. When irreversibility is combined with uncertainty over future returns and the opportunity to delay investment, only a positive expandability option exists, and this implies the optimal investment trigger is greater than the trigger given by the traditional net present value rule. Because the value of the expandability option increases in the level of uncertainty, the incentive for new investment is lower at higher levels of uncertainty.[1] This suggests a negative relationship between the current level of R&D investment and uncertainty.[2]

The type of capital investment also influences the nature of the uncertainty relevant to the investment decision. Private R&D is generally regarded as investment in knowledge-producing activities aimed at the discovery and market introduction of new products and processes. Uncertainty about future market returns to innovation will play a critical role in the decision to invest in R&D.[3] For instance, when new products are introduced into the marketplace, firms are uncertain about the acceptance by potential customers, the reliability of suppliers and production operations, and the reaction by rival firms. When these uncertainties are high, expandability options suggest that R&D investment will be delayed. This leads to our first hypothesis[4]:

> H1: The level of current R&D investment falls as the degree of uncertainty about returns to innovation increases.

One of the most significant sources of uncertainty about the returns to innovation is the competitive reaction by rivals. Although firms have a variety of actions available to reduce competitive uncertainty, obtaining legal protection through the patent system figures prominently.[5] By obtaining a patent, firms prevent current and potential competitors from selling an imitation of their innovation, which protects their revenue stream from business stealing effects. The idea that patent protection increases a firm's ability to appropriate the returns from its innovations is commonplace in the literature. The question that has received the most attention is how effective patent protection is as a means for appropriating returns.[6] To the degree that patent protection is effective, obtaining a patent should reduce the effect of market uncertainty on the firm's current R&D investment. This leads to our second hypothesis[7]:

[1] In addition to reducing the incentive for new investment, higher levels of uncertainty reduce the incentive to suspend or abandon ongoing investment projects. Because of these offsetting incentives, the effect of uncertainty on the current level of irreversible investment remains theoretically ambiguous, but does lead to a wider zone of investment inaction that may dampen any investment response to shocks. Bloom, Bond, and Van Reenen (2007) examine this "cautionary effect" theoretically and empirically. For further background, refer to Dixit (1992), Guiso and Parigi (1999), Abel and Eberly (1999), and Bloom (2008).

[2] Subsequent theoretical research has explored issues related to the firm's opportunity to delay investment. When investment has strategic value, Kulatilaka and Perotti (1998) find the value of growth options increases with the level of uncertainty and offsets (at least partially) the effect of expandability options on the incentive for current investment. Weeds (2002) considers a real options model with R&D competition and finds that the equilibrium depends on the balance between the value of delay and the expected benefit of preemption. Novy-Marx (2007) finds that investment decisions are delayed in a perfectly competitive market when firm-level opportunity costs and heterogeneity are important. Tobin's q-theory is the traditional approach to modeling R&D investment (see, for instance, Hall, 1992). Abel et al. (1996) link Tobin's q-theory and option pricing models of investment. They show that both approaches yield identical results when examining how uncertainty about future returns influences optimal investment.

[3] Pindyck (1993) presents an alternative model with uncertainty about costs. He finds that higher technical uncertainty leads to earlier investment, while higher input cost uncertainty leads firms to delay investment.

[4] Our literature search identified three prior studies examining the relationship between R&D investment and uncertainty. Czarnitzki and Toole (2007) use cross-sectional data on innovative firms in the German manufacturing sector to examine how R&D subsidies interact with product market uncertainty. Using the variance of revenue from new product sales, they find that current R&D investment falls as uncertainty increases and R&D subsidies partially offset the effect of uncertainty on the firm's R&D decision. Goel and Ram (2001) examine a panel of OECD countries and measure uncertainty using the standard deviation of each country's inflation rate. They find that uncertainty reduces the share of R&D in GDP. Minton and Schrand (1999) find that cash flow volatility is associated with lower levels of R&D investment using a sample of public companies drawn from Compustat.

[5] Mazzoleni and Nelson (1998) discuss the various economic theories for patent protection and review some of the early empirical literature.

[6] This observation is the starting point for a large theoretical and empirical literature that cannot be summarized in this paper. The empirical literature uses either survey data or patent renewal data to shed light on differences in patent effectiveness or patent value (see, for instance, Pakes, 1986). The literature examining the relation between patents and firm value is surveyed in Czarnitzki, Hall, and Oriani (2006). Also, since patenting involves the disclosure of information, the firm's decision to patent represents a trade-off between monopoly rents and disclosure. Thus, patents do not unambiguously induce R&D investment. Arora et al. (2008) discuss this issue, and Cohen (2005) surveys the arguments and evidence on appropriation.

[7] Investment in R&D that gets embodied in a patent can be (at least partially) recouped by selling the intellectual property rights. This partially offsets the irreversibility of R&D investment. In this sense, filing a patent can be thought of as purchasing a reversibility option on R&D investment. We thank an anonymous referee for making this point. See Bloom and Van Reenen (2002) for an analysis of patents as options.

H2: Patent protection mitigates the effect of uncertainty about the returns to innovation, thereby increasing the level of current R&D investment.

III. Data

Our main data source is the Mannheim Innovation Panel (MIP), a business survey that has been conducted by the Centre for European Economic Research (ZEW) in Mannheim, Germany, since 1992. The MIP is the German part of the European-wide Community Innovation Surveys (CIS) designed to collect harmonized data on innovation in the European Community following the guidelines of the OSLO manual, the international guidelines for collecting innovation data from the business sector (Eurostat and OECD, 2005).[8] The surveys yield a representative sample of the German manufacturing sector each year. Unless stated otherwise, all data used in the analysis are taken from the MIP surveys. In addition to the survey data, we collected information on firm-level patenting activity from the German Patent and Trademark Office. This database covers all German patents (including European Patent Office priority applications with German coverage) since 1978. We also collected credit rating information from Creditreform, the largest German credit rating agency, to gauge each firm's access to external financial capital, a control for potential financial constraints. Further, we collected information on industry-level concentration and sales from German official statistical reports of the Monopolies Commission.

Our analysis is based on an unbalanced panel of product-innovating firms in the manufacturing sector between 1995 and 2001. The panel structure is unbalanced because firms do not respond to the MIP survey every year. A product-innovating firm is defined to be a company that introduced at least one new product in the presample period, that is, before the firm enters our panel database. We require each firm to be observed at least three times before entering our panel database. These presample years, which vary from three to nine years depending on the firm, are used to generate our uncertainty measures and other predetermined covariates.[9] Our final sample has 2,340 firm-year observations corresponding to 566 product-innovating firms and has the following structure: 5% of the firms are observed for all seven years of our sample, about 28% are observed for five or six years, and the remaining 67% are observed for three or four years.

Identifying empirical measures of uncertainty at the firm-level is challenging. Firms may perceive uncertainty about market returns along a number of dimensions. To be completely consistent with theory, one would like a forward-looking measure of firm-specific uncertainty.[10] Because experience is one of the most important mechanisms for learning, a reasonable proxy can be constructed based on the firm's past market experience as innovators. We use revenue volatility from past market introductions as our proxy for firm-specific uncertainty. Consequently, we assume that past market experience is informative about how firms perceive uncertainty going forward. Their market experience as innovators, however, is not the same as their market experience with established products, which rely on more stable demand and supply relationships. Thus, we generate two firm-specific uncertainty measures using the coefficient of variation of past sales revenue: one capturing uncertainty related to innovation (UNC_NEW) and the other capturing uncertainty related to established products (UNC_OLD). This allows for two separate sources of uncertainty to affect R&D investment.

We make use of a question about the sales of new products that has been included in the surveys each year. Companies are first asked to indicate whether they introduced at least one new product in the past three years. Firms that answer yes are product innovators. Following an affirmative answer, each product innovator is asked to provide the share of total sales in year t that is due to new product introductions from t to $t - 2$. We use this information in combination with total sales to calculate the level of new product sales for each firm i in period t. The difference between total sales and new product sales gives the value of established product sales. These two variables are used to calculate the uncertainty measures as shown in equation (1) below.

We use the coefficient of variation as our measure of volatility (uncertainty) over time for both new product sales and established product sales for each firm. The procedure is the same for both types of sales. Before calculating the uncertainty measures for each firm year, we made two adjustments to a firm's sales volume. The first adjustment eliminates firm size effects. It takes the firm's sales in a particular year and divides it by the number of employees at the firm in that year. The second adjustment eliminates possible differences in trends, diffusion patterns, or product life cycle characteristics of particular industries. For instance, new product diffusion is expected to be more rapid in the electronics industry than in the steel industry due to differences in consumer or producer behavior or product characteristics within those industries. To make this adjustment, we first calculated the average sales per employee across all

[8] For a detailed description of the CIS, see Eurostat (2004).

[9] Note that we performed robustness tests of the regressions presented in the next section by restricting the time window used for the calculation of historical variables from three to six years. This did not affect any of the findings we present. Hence, we do not report detailed results from those regressions.

[10] In the empirical literature studying the relationship between investment in physical capital and uncertainty, researchers have used a variety of measures, each with its own strengths and weaknesses. Carruth et al. (2000) and Lensink et al. (2001) review these. Following Leahy and Whited (1996), three more recent studies use stock market volatility measures of uncertainty for publicly traded firms (Baum, Caglayan, & Talavera, 2007; Bloom et al., 2007; Bulan, 2005). Most of our firms are privately owned and not traded in the public market. Consequently, this type of uncertainty proxy is not possible in our context.

the firms in the industry for each year. Then we divided the individual firm's sales per employee by the industry average sales per employee. After these two adjustments, we calculated the coefficient of variation across time for each firm. The number of observations available for calculating the coefficients of variation for each firm relied on the presample data for which we have three to nine years available ($s = 1,\ldots, S$, with S ranging between 3 and 9):

$$UNC_{it} = \frac{\sqrt{\frac{1}{S}\sum_{s=1}^{S}\left[Z_{i,t-s} - \left(\frac{1}{S}\sum_{s=1}^{S} Z_{i,t-s}\right)\right]^2}}{\frac{1}{S}\sum_{s=1}^{S} Z_{i,t-s}}, \qquad (1)$$

$$\text{with} \quad Z_{it} = \frac{\frac{R_{it}}{L_{it}}}{\frac{1}{n_j}\sum_{i=1}^{n_j}\frac{R_{it}}{L_{it}}},$$

where Z_{it} is calculated as follows: R_{it}, which denotes the volume of new or established product sales of firm i in year t, is divided by L_{it}, the number of employees in firm i in year t. The resulting firm-level sales per employee (R_{it}/L_{it}) are normalized by the average sales per employee in firm i's respective industry j.

Because our proxy for firm-level uncertainty has not been used in published research, we would like to validate this measure against external information. Based on the measurement approach used by Guiso and Parigi (1999), we searched for survey data. Somewhat fortunately, the 2005 German Community Innovation Survey asked a representative (random) sample of manufacturing firms to describe the competitive situation in their main product markets in 2004. The survey asked six questions, each allowing four possible choices: "Does not apply," "Does somewhat apply," "Does apply," and "Does strongly apply." Two of the six questions addressed the firm's perceived level of uncertainty in its main product market. The first of these referred to uncertainty about rivalry. It stated, "Reactions by competitors are difficult to anticipate." The second of these referred to uncertainty about demand: "The development of demand is difficult to forecast." Although the survey responses cannot be linked to the firms in our sample, we decided to examine the relationship between our uncertainty measure and the survey responses at the industry level. Using nineteen industry categories, we created a dummy variable equal to 1 if the survey respondent answered, "Does strongly apply," to each of the two scenarios. As a rough validation of our proxy, we calculated the correlation coefficient between our measure of uncertainty, the volatility of new product sales, and the average values for each of the dummy variables indicating strategic or demand sources of uncertainty at the industry level.

The results are generally supportive of our proxy. The correlation coefficient between our uncertainty measure and the external survey data is 0.43 for the product market rivalry question and 0.45 for the demand uncertainty question. While correlation values such as these are usually interpreted as indicating a moderate degree of relatedness, it should be remembered that these alternative measures were drawn from two independent data sets and represent two completely different approaches to measuring firm-level uncertainty.[11] Scatter plots showing these relationships can be found in the appendix.

The dependent variable is R&D expenditure at the firm level ($R\&D_i$) in millions of deutsche marks (1.95583 DM = 1 EURO). Although we consider only previous product innovators, we find that more than one-third of the firm-year observations on R&D have a value of 0. This is due to the fact that our sample contains many small firms that might conduct R&D only intermittently (the median number of employees per firm in our sample is 110). It is also possible, however, that these firms chose not to invest in R&D because of uncertainty about their future market revenues, which is consistent with the predictions from real options theory (see, for instance, the discussion of hysteresis in Dixit, 1992). Our econometric analysis takes this into account by modeling the censored distribution of R&D. Above 0, the distribution of R&D spending is quite skewed, and this motivates our logarithmic specification ($\ln R\&D_i$). Since we cannot take the log of the censored observations at $R\&D_i = 0$, we set those observations to the minimum observed positive R&D value in the sample and interpret this observed minimum as the censoring point in the regression models.

The traditional investment literature, based on the capital asset pricing model (CAPM), suggests a negative relationship between nondiversifiable or systematic uncertainty and firm-level investment to the extent that firm-level returns are correlated with aggregate volatility. Since our sample has a large proportion of private firms, we cannot follow the standard approach of calculating firm-specific betas and constructing a proxy of systematic uncertainty. As an alternative, we generated an uncertainty measure at the detailed three-digit NACE industry level from official statistics from the German government.[12] We calculated the coefficient of variation for total industry sales (UNC_IND_{it-1}). This is included in our regressions as a control for systematic uncertainty that could influence firm-level R&D invest-

[11] We also examined the industry-level correlation between our new product market uncertainty measure and stock price volatility of publicly traded German firms. We cannot do this at the firm level because very few of our sample firms are publicly traded. The correlation between the two uncertainty measures at the industry level was positive, but moderate, with a value of 0.36.

[12] NACE is the European standard industry classification. As we do not have information about employment at this detailed industry level, we normalize industry sales not by the number of employees but by the number of firms active in that industry in a given year. The 566 firms in our sample operate in eighty different three-digit NACE industries.

ment. We also have annual time dummy variables in all regressions to account for macroeconomic shocks affecting R&D investment.

Another potential confounder in the relationship between investment and uncertainty is the risk aversion of the firm. If firms are risk averse, investment is expected to fall as uncertainty increases independent of any real options mechanism. To control for this possibility, we postulate that each firm's innovation strategy reflects its risk preferences. That is, firms with an aggressive product innovation strategy should be the least risk-averse firms, while those following a conservative innovation strategy should be the most risk averse. We included a control variable in the analysis for the firm's relative innovativeness in its industry. The firm's relative innovativeness (*PASTINNO*) is calculated using its average share of new product sales in the presample period (the same period over which we calculate our uncertainty measure). In addition, the firm-specific effect in the panel data models should also control for risk preferences to the extent these are time constant in our sample period.

To control for firm-level innovation capabilities, we used the firm's lagged patent stock per 100 employees, $PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$, where the stock is calculated from the patent database for each firm since 1978 using a 15% annual obsolescence rate of knowledge (see Griliches & Mairesse, 1984, or Hall, 1990, for details). As mentioned above, it controls for a firm's prior patenting and R&D capabilities, which are expected to stimulate current R&D investment due to either productivity differences or perceived growth options. To test hypothesis 2, we interact the patent stock per employee with new product market uncertainty.

Market type and the degree of competition may also influence the firm's investment decision. We controlled for market type using ten industry dummy variables. To measure the degree of competition, we included each market's seller concentration using the Herfindahl index based on shares of total market sales at the three-digit NACE level, ln(*HHI*).[13]

With regard to other firm characteristics, we included controls for firm size and liquidity constraints. The number of employees controls for heterogeneity in size with respect to the propensity to conduct R&D. We included two controls for potential liquidity constraints. For access to external capital, we used the firm's credit rating, ln(*RATING*), lagged one period.[14] The rating is an index ranging from 100 to 600, where 600 is the worst and essentially corresponds to bankruptcy of the firm. For the availability of internal capital, we used a measure of the firm's average price-cost margin, (*PASTPCM*), in the presample period:[15]

Table 1.—Descriptive Statistics (2,340 Firm-Year Observations, 566 Firms)

Variable	Mean	s.d.	Minimum	Maximum
$R\&D_{it}$	7.701	60.805	0	1,064.697
$UNC\_NEW_{i,t-1}$	0.955	0.685	0.018	3.000
$UNC\_OLD_{i,t-1}$	0.532	0.375	0.016	2.449
$UNC\_IND_{i,t-1}$	0.117	0.100	0.015	1.067
$PASTINNO_{i,t-1}$	39.680	26.005	0.125	99.167
$PASTPCM_{i,t-1}$	0.275	0.137	−0.373	0.827
$EMP_{i,t-1}$	484.931	2,129.150	1	40,000.000
$PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$	1.856	4.598	0	37.047
$HHI_{i,t-1}$	47.915	68.595	3.213	432.041
$RATING_{i,t-1}$	215.882	62.973	100	600.000

Ten industry dummy variables and six time dummy variables are not presented.

$$PASTPCM_{i,t-1} = \frac{1}{S}\sum_{s=1}^{S} PCM_{i,t-s} \tag{2}$$

with PCM = (Sales – staff cost – material cost + R&D) / Sales, where the presample period corresponds to the period used for the uncertainty measure.

Finally, six time dummy variables absorb macroeconomic shocks that could have affected R&D investment decisions during the sample period. Table 1 presents descriptive statistics of all variables. Note that all time-varying variables enter the right-hand side of the regression models as lagged values, so that they can be treated as predetermined.

IV. Estimation Results

A. Main Results

We employ two different models with our panel data: a pooled cross-sectional approach and a random effects panel estimator. The model can be written as

$$\begin{aligned} y_{it} &= \max(0, x_{it}\beta + c_i + u_{it}), \quad i = 1, 2, \ldots, N, \\ t &= 1, 2, \ldots, T, \quad u_{it}|x_{it}, c_i \sim N(0, \sigma_u^2), \end{aligned} \tag{3}$$

where y_{it} is the dependent variable, x_{it} denotes the set of regressors, β is a vector of parameters to be estimated, c_i is the unobserved firm-specific effect, and u_{it} is the error term. We estimated two versions of this model. First, we assume that $c_i = 0$, and thus the model can be estimated as a pooled cross-sectional model where we adjust the standard errors for firm clusters to account for the panel structure of the data. The pooled model has the advantage that it is not necessary to maintain the strict exogeneity assumption. While u_{it} must be independent of x_{it}, the relationship

[13] As an alternative measure for market power, we also used the firms' market shares at the three-digit NACE industry level. Because the results never changed, we omit a detailed presentation of regressions using market share instead of the Herfindahl index.

[14] For some firms, there was no rating available for the preceding year. In such cases, we used ratings from one or two years earlier.

[15] See Collins and Preston (1969) or Ravenscraft (1983). Scholars who have used such measures to test for financial constraints typically add back R&D to PCM because R&D is an expense and reduces profits in the period. If the firm had not decided to invest in R&D, PCM would have been accordingly higher and is therefore corrected by current R&D in most empirical studies (see, for example, Harhoff, 1998).

TABLE 2.—TOBIT REGRESSIONS ON ln(R&D$_{it}$), 1995–2001

Variable	Model A: Pooled Cross-Sectional Tobit[a]	Model A: Random-Effects Panel Tobit	Model B: Pooled Cross-Sectional Tobit[a]	Model B: Random-Effects Panel Tobit
$UNC\_NEW_{i,t-1}$	−4.100***	−2.692***	−4.165***	−2.772***
	(0.390)	(0.375)	(0.393)	(0.376)
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)]$			0.145***	0.101**
			(0.054)	(0.051)
$UNC\_OLD_{i,t-1}$	−0.364	−0.228	−0.464	−0.289
	(0.523)	(0.496)	(0.522)	(0.496)
$UNC\_IND_{i,t-1}$	2.276	1.908	2.314	1.907
	(1.796)	(1.455)	(1.796)	(1.455)
$PASTINNO_{i,t-1}$	0.018*	0.029***	0.020*	0.030***
	(0.011)	(0.011)	(0.011)	(0.011)
$PASTPCM_{i,t-1}$	1.614	1.024	1.627	1.065
	(1.152)	(1.169)	(1.148)	(1.165)
$\ln(EMP_{i,t-1})$	1.314***	1.385***	1.319***	1.389***
	(0.113)	(0.116)	(0.112)	(0.116)
$PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$	0.107***	0.113***	0.029	0.058
	(0.022)	(0.029)	(0.030)	(0.040)
$\ln(HHI_{i,t-1})$	−0.139	0.069	−0.133	0.072
	(0.167)	(0.162)	(0.167)	(0.161)
$\ln(RATING_{i,t-1})$	0.485	0.112	0.405	0.089
	(0.690)	(0.595)	(0.686)	(0.594)
Intercept	−13.671***	−14.688***	−13.241***	−14.528***
	(4.293)	(3.642)	(4.272)	(3.634)
Joint significance of industry dummies ($\chi^2(10)$)	50.84***	51.29***	49.35***	50.56***
Joint significance of time dummies ($\chi^2(6)$)	105.70***	123.90***	105.97***	124.81***
Log likelihood	−4,910.65	−4,726.83	−4,905.37	−4,725.00
McFadden R^2	0.141	0.173	0.142	0.173
Number of observations	2,340	2,340	2,340	2,340

Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%).
[a]Standard errors are clustered at the firm-level (566 clusters).

between u_{it} and x_{is}, $t \neq s$, is not restricted (see Wooldridge, 2002). For instance, the model allows for feedback of R&D in period t to the regressors in future periods. In the second version of the model, we assume there is firm-level heterogeneity, $c_i \neq 0$, and apply a random-effects tobit panel estimator. Consistency of the random-effects model requires the strict exogeneity assumption, that is, the error term has to be uncorrelated with the covariates across all time periods. In addition, the random-effects tobit requires the assumption that c_i is uncorrelated with x_{it}. Due to these stronger assumptions, we do not necessarily consider the panel specification as superior to the pooled cross-sectional results. It allows for unobserved firm-specific effects, but at the cost of more restrictive assumptions otherwise. Note that we keep the time-invariant regressors (industry dummy variables) in the random-effects panel model in order to reduce the error variance of the firm-specific effect.

For fixed-effects tobit models, the maximum likelihood estimator is not consistent (see Cameron & Trivedi, 2005). In the appendix, we present robustness checks using the entry stock count data estimator proposed by Blundell, Griffith, and Van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002) which allows for correlation between c_i and x_{it}.

Table 2 presents our regression results. We consider two versions of the empirical specification: model A excludes the interaction term between market uncertainty and patent protection in order to test the idea that market uncertainty reduces R&D investment (hypothesis one). Model B includes the interaction term to test hypothesis 2 that patenting mitigates the effect of uncertainty and thereby leads to greater current R&D investment.

The results for model A can be seen in columns 2 and 3 of table 2. Each of the specifications include the proxies for uncertainty in new and established product markets. In both the pooled- and random-effects models, uncertainty in new product markets significantly reduces current firm-level R&D investment. This is consistent with the prediction of real options theory as well as prior research on R&D and physical capital investment (these studies are referred to in footnotes 4 and 10). The partial effect of uncertainty in established product markets is negative, but not significantly different from 0 in either the pooled or random effects models.

Looking at the control variables in model A, our proxy for systematic risk (UNC_IND) is positive but not significantly different from 0. This suggests that the CAPM mechanism is not an important determinant of R&D investment, although the time dummy variables are significant and these could be capturing the effect of systematic uncertainty. In the literature, Leahy and Whited (1996) and Bulan (2005) do not find evidence supporting a CAPM effect for irreversible physical capital investment. Our control for firm-level risk preferences (PASTINNO) is significant and shows the expected sign: R&D investment increases as firms pursue more aggressive innovation strategies. The availability of internal finance (PASTPCM) and access to external financing are both positive, but neither is statistically significant. Larger firms invest more in R&D, and firms with better R&D capabilities invest more. Both the industry dummies reflecting differences in R&D investment across market types and the time dummies are jointly significant in all regressions.[16]

Model B includes the interaction term between uncertainty and patenting, which allows the effect of uncertainty on R&D investment to depend on the firm's patent stock per employee. The results for model B can be seen in columns 4 and 5 of table 2. This interaction term is positive and significant in both the pooled- and random-effects models. This shows that R&D investment by patenting firms is less sensitive to uncertainty in new product markets. Patenting, however, does not completely offset the influence of uncertainty on R&D investment. This is expected since patent protection reduces perceived uncertainty about competitive rivalry but does not address other forms of uncertainty that might be important, such as customer acceptance or supplier and production shocks.[17]

To evaluate the magnitude of the estimated uncertainty effects, we calculated marginal effects using the change in the expected value of $Y_{it} = \ln(R\&D_{it})$ (see Greene, 2003, for $E(Y|X)$ in the Tobit model). Because our model is formulated using the log of R&D investment, the difference in expected values approximates the growth in R&D due to a change in uncertainty. Suppose, for instance, that a nonpatenting firm (zero patent stock) faces the median level of uncertainty. If the uncertainty increased by 10% from the median, the effect on R&D investment would be

$$E[Y|X, UNC\_NEW + 10\%] - E[Y|X, UNC\_NEW] = -0.23. \qquad (5)$$

When the pooled model B is used, a 10% increase in uncertainty (taken from the median value of uncertainty and fixing all other covariates at their median values as well) leads to a reduction of R&D investment by 23%, a sizable impact.

Schankerman (1998) suggests calculating the equivalent subsidy rate (ESR) as a measure of the private value of patent rights. ESR answers the question: "If patent protection were eliminated, what cash subsidy would have to be paid to firms performing R&D to yield the same level of R&D?" (Schankerman, 1998, p. 95). Using the estimates from pooled model B, we conduct a slightly different counterfactual exercise: if a nonpatenting firm responded to uncertainty in the same way as a firm with a median level of patent protection (all else constant), what is the implied percentage increase in R&D investment?[18] This exercise suggests that patent protection confers a 20% increase in R&D investment. While simple, our 20% ESR estimate for German firms is not out of line with other ESR estimates based on completely different methods. Using patent renewal data, Lanjouw (1998) shows simulation results for four West German technology groups. Her ESR estimates range from about 12% to 15% for engines, computers, and pharmaceuticals. Her fourth group, textiles, was quite different, with an ESR estimate of 75.4%. Using patent renewal data for France, Schankerman (1998) reports a weighted average ESR for company-funded R&D of 24%.[19] Finally, Arora, Ceccagnoli, and Cohen, (2008) use the 1994 Carnegie Mellon Survey of R&D performing units in U.S. manufacturing and find an average ESR of 33%.

B. *Robustness Checks: IV Analysis*

Our firm-level measure of new product market uncertainty is constructed from each firm's sales of new products in the years before their current R&D investment decision. This measure is predetermined because it is constructed from past market performance, but it is possibly correlated with unobserved firm-specific factors that affect current R&D. To examine this possibility, we required an instrumental variable (IV) that is exogenous, meaning it is uncorrelated with any unobserved firm-specific factors affecting the firms' current R&D decisions, and relevant, meaning it has strong partial correlation with our uncertainty measure in a reduced form regression to avoid weak instrument bias.

After extensive searching for instrumental variables, we found two instruments that satisfy the Staiger and Stock (1997) guideline for avoiding weak instrument bias in IV: the average volatility of new product sales in Germany at the industry level and the change in U.S. employment at the industry level from the Compustat database.[20] These industry-level IVs are exogenous to unobserved firm-specific factors that affect an individual firm's current R&D decision and passed the overidenification test described below.

Column 2 of table 3 shows the first-stage results from regressing UNC_NEW on all covariates and our instruments. In case of weak instruments, the coefficient esti-

[16] The results for the control variables in model B are essentially the same. To save space, we will not discuss them separately.

[17] Using OECD data, Kanwar and Evenson (2003) find that intellectual property rights significantly increase R&D investment as a share of gross national product.

[18] The calculation is analogous to equation (5), but instead of using a 10% of uncertainty, we calculate the difference between a nonpatenting firm and a firm with a median level of patent protection, all else constant.

[19] Schankerman (1998) discusses a variety of ESR estimates found using patent renewal data. There appear to be fairly substantial differences across countries and technology fields. We present an estimate for a median manufacturing firm in Germany between 1995 and 2001.

[20] To use the U.S. Compustat data, we had to map European NACE and U.S. SIC industry classifications. This was feasible only at a two-digit industry level. By itself, the U.S. industry instrument was not strong enough to meet the Staiger and Stock (1997) guideline to avoid weak instrument bias in IV.

TABLE 3.—IV REGRESSIONS ON ln(R&D$_{it}$), 1995–2001

Variable	First Stage: OLS on UNC_NEW	Second Stage: Tobit with First-Stage Residuals (Bundell-Smith endogeneity test)	Second Stage: Newey's IV FIML Tobit
$UNC\_NEW_{i,t-1}$		−4.247***	−4.248***
		(1.097)	(1.109)
$UNC\_OLD_{i,t-1}$	0.631***	−0.262	−0.262
	(0.050)	(0.832)	(0.838)
$UNC\_IND_{i,t-1}$	0.174	2.324	2.325
	(0.172)	(1.807)	(1.807)
$PASTINNO_{i,t-1}$	−0.023***	0.014	0.014
	(0.001)	(0.027)	(0.027)
$PASTPCM_{i,t-1}$	−0.240**	1.573	1.572
	(0.108)	(1.184)	(1.184)
$\ln(EMP_{i,t-1})$	−0.062***	1.304***	1.304***
	(0.012)	(0.136)	(0.137)
$PSTOCK_{i,t-1}/EMP_{i,t-1}$	−0.005	0.106***	0.106***
	(0.003)	(0.023)	(0.023)
$\ln(HHI_{i,t-1})$	0.021	−0.141	−0.141
	(0.016)	(0.169)	(0.169)
$\ln(RATING_{i,t-1})$	0.063	0.492	0.492
	(0.053)	(0.696)	(0.696)
IV: ΔUS_EMP_{it}	0.008*		
	(0.005)		
IV: (industry avg. $UNC\_NEW)_{t-1}$	0.465***		
	(0.045)		
First-stage residuals		0.162	
		(1.106)	
Intercept	0.933***	−13.431***	−13.429***
	(0.334)	(4.539)	(4.551)
Joint significance of industry dummies	F(10,565) = 1.04	$\chi^2(10) = 50.00$***	$\chi^2(10) = 49.89$***
Joint significance of time dummies	F(6,565) = 0.82	$\chi^2(6) = 105.14$***	$\chi^2(10) = 104.95$***
R^2	0.704	–	–
Number of observations	2,340	2,340	2,340

Clustered standard errors in parentheses (566 firm-level clusters).
*** (**,*) indicate a significance level of 1% (5%, 10%).

mates in IV regressions can be seriously biased. To avoid this problem, Staiger and Stock (1997) suggest that the partial F statistic for the IVs must exceed a value of 10. In our case, the value of this statistic is $F(2{,}565) = 54.42$, which clearly rejects a weak instrument concern.

Next, we tested whether *UNC_NEW* is endogenous in the structural equation using the Smith and Blundell (1986) method for tobit models, which is similar to the Rivers-Vuong procedure for the probit case. It requires computing the residuals from the first-stage reduced-form regression and subsequently plugging these residuals into the tobit estimation of the R&D equation. The usual t-statistic on the coefficient of the first-stage residuals provides a robust test of the null hypothesis that *UNC_NEW* is exogenous. If the coefficient estimate is significantly different from 0, meaning the exogeneity of *UNC_NEW* is rejected, the second-stage tobit standard errors would not be asymptotically valid. In addition to this test, we estimate a full information maximum likelihood (FIML) IV tobit as proposed by Newey (1990).

As can be seen in column 3 of table 3, the first-stage residuals are not significant in the R&D equation (t-value $= 0.15$, p-value $= 0.885$), which leads to the conclusion that the exogeneity of *UNC_NEW* is not rejected in the R&D equation. The results for Newey's FIML IV tobit model can be seen in column 4 of table 3. Consistent with the fact that we did not reject the exogeneity of *UNC_NEW*, the results are virtually the same as those of the Smith-Blundell procedure. There is no evidence that *UNC_NEW* is endogenous.

We also tested the exogeneity of the instrumental variables. Note, however, that there is no standard overidentification test for tobit models as there is for linear models. Therefore, we can perform a test only by ignoring the left censoring of the R&D variable. We used a standard two-stage least squares (2SLS) model and computed Hansen's J test (the heteroskedasticity-robust version of the Sargan test). The Hansen J statistic is $\chi^2(1) = 2.62$ (p-value $=$ 0.11) indicating that our IVs satisfy the exogeneity requirement.

C. *Robustness Checks: Differences in Firm Patenting Behavior*

It is well documented that the distribution of patenting across firms is highly skewed, even in the manufacturing sector. For this reason, one may be concerned that the positive and significant coefficient estimate for the interaction term between the patent stock per employee and uncertainty may be driven by a few firms that patent heavily. As a robustness check, we split the firms in our sample into four groups and estimated four different slope coefficients for the interaction term. The first group refers to nonpatenting firms:

Group 1: $PS0\_UNC\_NEW = UNC\_NEW \times D(PSTOCK/EMP = 0)$.

For patenting firms, we defined three evenly distributed groups according to the quantiles of their patent stock distribution: low, medium, and high patent stock per employee. Let Q_{33} and Q_{67} represent the 33% and 67% quantiles of the patent stock distribution, respectively.

Group 2: $PSLOW\_UNC\_NEW = UNC\_NEW \times D(PSTOCK/EMP > 0) \times D(PSTOCK/EMP < Q_{33})$
Group 3: $PSMED\_UNC\_NEW = UNC\_NEW \times D(PSTOCK/EMP > 0) \times D(PSTOCK/EMP > Q_{33}) \times D(PSTOCK/EMP < Q_{67})$
Group 4: $PSHIGH\_UNC\_NEW = UNC\_NEW \times D(PSTOCK/EMP > 0) \times D(PSTOCK/EMP > Q_{67})$

Table 4 shows the regression results with these new variables added to the specifications used previously. We find that the estimated slope coefficients for these new interaction variables decrease monotonically with increasing patent stocks per employee. That is, the more patents a firm holds (relative to its size), the less it responds to product market uncertainty. A joint test of the null hypothesis that the four slope coefficients are equal is rejected at a 1% significance level (see the bottom of table 4). These results suggest that the mitigating effect of patenting on the R&D investment-uncertainty relationship is not due to either a self-selection effect into patenting or any subgroup of patenting firms.

TABLE 4.—TOBIT REGRESSIONS ON ln(R&D$_{it}$), 1995–2001

Variable	Pooled Cross-Sectional Tobit[a]	Random-Effects Panel Tobit
$PS0\_UNC\_NEW_{i,t-1}$	−4.196***	−2.949***
	(0.403)	(0.382)
$PSLOW\_UNC\_NEW_{i,t-1}$	−3.958***	−2.278***
	(0.585)	(0.478)
$PSMED\_UNC\_NEW_{i,t-1}$	−3.031***	−1.750***
	(0.601)	(0.513)
$PSHIGH\_UNC\_NEW_{i,t-1}$	−2.203***	−1.177*
	(0.674)	(0.677)
$UNC\_OLD_{i,t-1}$	−0.503	−0.319
	(0.514)	(0.495)
$UNC\_IND_{i,t-1}$	2.302	1.820
	(1.723)	(1.455)
$PASTINNO_{i,t-1}$	0.022**	0.032***
	(0.011)	(0.011)
$PASTPCM_{i,t-1}$	1.697**	1.089
	(1.136)	(1.163)
$\ln(EMP_{i,t-1})$	1.274***	1.312***
	(0.116)	(0.119)
$PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$	0.044*	0.066*
	(0.023)	(0.034)
$\ln(HHI_{i,t-1})$	−0.149	0.059
	(0.170)	(0.161)
$\ln(RATING_{i,t-1})$	0.386	0.093
	(0.670)	(0.593)
Intercept	−12.894***	−13.975***
	(4.201)	(3.629)
Joint significance of industry dummy variables ($\chi^2(10)$)	47.17***	46.59***
Joint significance of time dummy variables ($\chi^2(6)$)	103.77***	125.96***
Joint test on difference of slope coefficients of UNC_NEW ($\chi^2(3)$)	12.87***	13.67***
Log likelihood	−4,899.52	−4,720.09
McFadden R^2	0.143	0.174
Number of observations	2,340	2,340

Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%).
[a]Standard errors are clustered at the firm-level (566 clusters).

D. Robustness Checks: Differences in Patent Effectiveness

It is also well known from survey data that patenting is only one mechanism that manufacturing firms use to appropriate the returns from their R&D investments (Cohen, Nelson, & Walsh, 2000). In some manufacturing industries, such as food and publishing, patenting is not as important as it is in other manufacturing industries such as pharmaceuticals and electronics. Recall from hypothesis 2 that obtaining a patent should reduce the effect of market uncertainty on the firm's current R&D investment decision only to the extent that patent protection is an effective means of appropriation.[21] Clearly, when patenting is not an effective means of protection, it cannot mitigate the effect of product market uncertainty.

To examine this issue further, we grouped industries into high, medium, and low patent effectiveness categories based on the 1994 Carnegie Mellon Survey as reported in Cohen et al. (2000) and estimated separate slope coefficients for the interaction term.[22] Because the mitigating effect of patenting depends on the patent effectiveness, the coefficient and statistical significance of the interaction term should be greatest for those firms in the high patent effectiveness industries. In the group of industries with high patent effectiveness, we included pharmaceuticals, electronics, vehicles, and information technologies. In the medium group, we included industries such as chemicals, paper, precision instruments,

[21] In the Cohen et al. (2000) survey, patent effectiveness was defined to be the degree to which patents protected the firm's competitive advantage.

[22] We used the results for the average percentage of product innovations for which patents were considered effective (table 1 of Cohen et al., 2000) for the grouping. This source could only serve as a guide because there were differences in coverage and classification between their survey results and our sample industries.

TABLE 5.—PATENTING EFFECTIVENESS ROBUSTNESS CHECKS

Variable	Model C: Pooled Cross-Sectional Tobit[a]	Model C: Random-Effects Panel Tobit	Model D: Pooled Cross-Sectional Tobit[a]	Model D: Random-Effects Panel Tobit
$UNC\_NEW_{i,t-1}$	−4.133***	−2.745***	−4.177***	−2.783***
	(0.391)	(0.375)	(0.393)	(0.376)
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)] \times HIGH$	0.320***	0.334***		
	(0.068)	(0.089)		
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)] \times MEDIUM$	0.182**	0.220**		
	(0.092)	(0.106)		
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)] \times LOW$	0.081*	0.013		
	(0.043)	(0.067)		
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)] \times D(CRUCIAL = 1)$			0.242***	0.214**
			(0.069)	(0.093)
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)]$			0.217	−0.027
$\times D(CRUCIAL = MISSING)$			(0.251)	(0.225)
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)] \times D(CRUCIAL = 0)$			0.134***	0.087
			(0.051)	(0.053)
$UNC\_OLD_{i,t-1}$	−0.533	−0.378	−0.466	−0.303
	(0.522)	(0.496)	(0.522)	(0.496)
$UNC\_IND_{i,t-1}$	2.655	2.084	2.285	1.902
	(1.805)	(1.451)	(1.794)	(1.454)
$PASTINNO_{i,t-1}$	0.023**	0.033***	0.020*	0.030***
	(0.011)	(0.011)	(0.011)	(0.011)
$PASTPCM_{i,t-1}$	1.483	0.883	1.532	0.964
	(1.151)	(1.164)	(1.159)	(1.166)
$\ln(EMP_{i,t-1})$	1.298***	1.369***	1.303***	1.376***
	(0.113)	(0.116)	(0.113)	(0.116)
$PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$	0.016	0.030	0.014	0.047
	(0.028)	(0.044)	(0.027)	(0.042)
$\ln(HHI_{i,t-1})$	−0.130	0.074	−0.126	0.069
	(0.166)	(0.161)	(0.167)	(0.162)
$\ln(RATING_{i,t-1})$	0.343	0.056	0.351	0.040
	(0.680)	(0.593)	(0.687)	(0.595)
Intercept	−12.799***	−14.231***	−9.925***	−10.759***
	(4.239)	(3.630)	(4.101)	(3.572)
Joint significance of industry dummy variables ($\chi^2(10)$)	46.17***	47.95***	49.22***	50.76***
Joint significance of time dummy variables ($\chi^2(6)$)	106.33 ***	127.10***	106.31***	126.08***
Log likelihood	−4,899.61	−4,718.56	−4,904.01	−4,723.71
McFadden R^2	0.143	0.175	0.142	0.174
Number of observations	2,340	2,340	2,340	2,340

Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%).
[a]Standard errors are clustered at the firm-level (566 clusters).

glass, and fabricated metals. In the low group, we included industries such as textiles, food, publishing, clothing, and so forth.

Before presenting the results for the industry groupings, we were also able to examine differences in patent effectiveness at the firm level, at least partially. Two of the MIP surveys, one in 1992 and another in 2001, asked firms to indicate the importance of patent protection for their business. If the respondents marked the highest category of importance, indicating that patents were crucial to their business, we created a dummy variable that is equal to 1 and 0 otherwise. We merged that variable at the firm level to our sample. For almost 90% of our sample firms, we had a survey response. For 14% of our sample firms, patent protection was crucial, and for 75% of these firms, it was not. For the remaining 11%, we have no information from the surveys. Consequently, we construct three interaction terms:

$UNC \times PS \times D(CRUCIAL = 1)$, which estimates the slope of the mitigating effect of patents for firms that rated patent protection as crucial

$UNC \times PS \times D(CRUCIAL = 0)$ which estimates the slope of the mitigating effect of patents for firms that rated patent protection as something other than crucial

$UNC \times PS \times D(CRUCIAL =$ "$MISSING$"$)$, which estimates the slope of the mitigating effect of patents for firms where we do not have information (PS is shorthand for patent stock).

Table 5 presents the regression results for the industry and firm-level groupings by level of patent effectiveness. Using the same control variables as before, we estimated pooled- and random-effects tobit models. For the industry groupings, model C in columns 2 and 3 of table 5, we see the expected result that the magnitude of the mitigating effect of patenting on the R&D investment-uncertainty relationship declines as patenting becomes increasingly less effective as a means to appropriate the returns to R&D investment. For industries where patents are highly effective, the coefficient on the interaction term is stable across models at about 0.32 and is statistically significant at a 1% level. For the low patent effectiveness industries, the coefficient estimate is still positive, but relatively small and only marginally significant at best. The mitigating effect of patents remains economically and statistically significant in the medium effectiveness industries. A Wald test soundly rejects the null hypothesis of equality of the coefficients across the three groups in both models.

The firm-level regression models in columns 4 and 5 of table 5 also support the mitigating effect of patenting for firms that responded in the survey that patent protection was crucial to their businesses. For this group, the coefficient estimates are economically and statistically significant in both the pooled- and random-effects models. For the firms that responded that patenting was not crucial, the pooled model shows a positive and significant coefficient, but this becomes insignificant in the random-effects panel model. For the firms with missing survey responses, the coefficient estimates are not significant in either model. Overall, both these results and the industry groupings discussed above support hypothesis 2 subject to the qualification that patenting must have some effectiveness for protecting the firm's competitive advantage.

V. Conclusion

This paper examined how uncertainty about future market returns to innovation influences current R&D investment and how this influence is affected by patent protection. We highlighted one mechanism through which patent protection may improve appropriability and stimulate R&D investment: patent protection reduces the firm's sensitivity to market uncertainty, decreases the value of waiting, and leads to greater current R&D investment. Our results show that higher levels of uncertainty reduce current R&D investment, with a nonpatenting firm in the German manufacturing sector reducing R&D investment by 23% in response to a 10% increase in uncertainty from the median. Patent protection offsets part of the firm's sensitivity to uncertainty and leads to greater current R&D investment when patenting is an effective means to appropriate the returns to R&D investment. Our estimates suggest the ex post private value of patent rights for a median firm in our sample is about 20% of its total R&D investment.

Our analysis is not without limitations. First, we must emphasize that we study innovative firms in the manufacturing sector. One must be cautious and not generalize our findings to noninnovative firms or to other sectors like services or agriculture. At this point, more research is needed before valid generalization can be done. Second, it would be beneficial to explicitly model the relationship between the use of intellectual property rights and different forms of uncertainty that firms face. Due to data limitations, we are not able to investigate this deeply in our setting. It would be necessary to have long time series data to calculate uncertainty measures and analyze how these interact with the decision to patent. Third, we show that the sensitivity to uncertainty is reduced the more patents a firm holds, but we are not able to investigate strategic motives for patenting or how multiple patents held by a firm interact with each other. For instance, it would be interesting to incorporate issues related to patent thickets or fencing in more detail. Furthermore, our uncertainty measures are generated from historical data. While it is reasonable to believe that firms build expectations on past experience, it would be desirable to have an explicitly forward-looking perception of uncertainty.

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APPENDIX

External Validation of the Uncertainty Proxy

As described in the text, the responses from an independent firm-level survey of perceived demand and strategic uncertainty were used to externally validate our uncertainty proxy. The independent survey data were compared with our proxy at the industry level. Figures A1 and A2 illustrate the linear relationships between our proxy, which is based on the volatility of new product sales, and the two alternative survey-based measures.

Robustness Check: The Entry Stock Poisson Estimator

Our preferred estimator would allow for dynamic feedback, (that is, not impose strict exogeneity), control for unobserved firm heterogeneity, and allow for correlation between the firm effect and the explanatory vari-

FIGURE A1.—SCATTER PLOT OF DEMAND UNCERTAINTY AND NEW PRODUCT SALES UNCERTAINTY

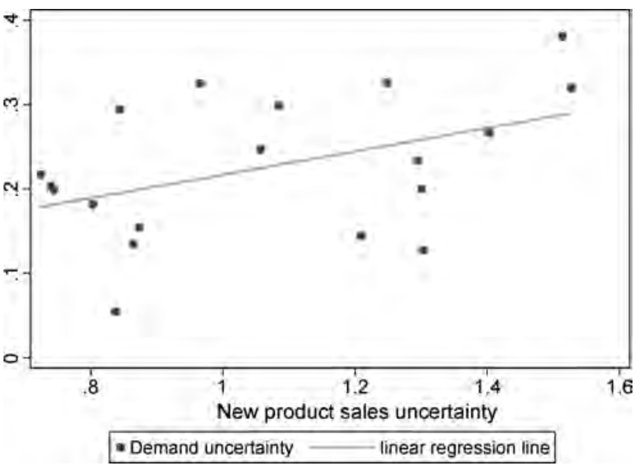

FIGURE A2.—SCATTER PLOT OF RIVALRY UNCERTAINTY AND NEW PRODUCT SALES UNCERTAINTY

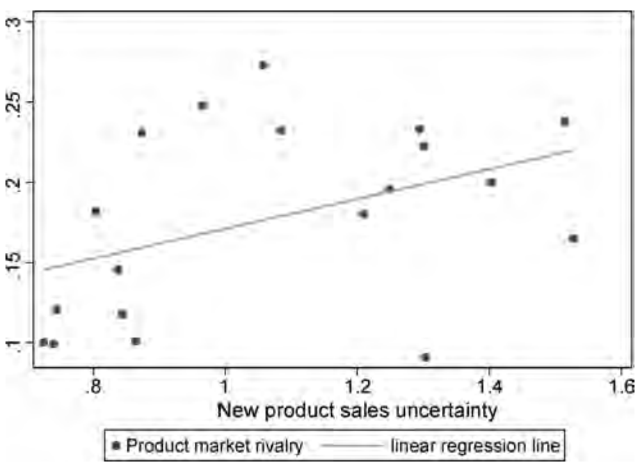

TABLE A1.—ENTRY STOCK POISSON ESTIMATOR: DEPENDENT VARIABLE: R&D INTENSITY

Explanatory Variables	Model A	Model B
$UNC\_NEW_{i,t-1}$	−0.282**	−0.354**
	(0.139)	(0.144)
$UNC\_NEW_{i,t-1} \times [PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)]$		0.038***
		(0.012)
$UNC\_OLD_{i,t-1}$	−0.072	−0.102
	(0.140)	(0.140)
$UNC\_IND_{i,t-1}$	0.136	0.137
	(0.613)	(0.651)
$PASTINNO_{i,t-1}$	0.001	0.002
	(0.003)	(0.003)
$PASTPCM_{i,t-1}$	0.365	0.335
	(0.312)	(0.316)
$\ln(EMP_{i,t-1})$	0.035	0.032
	(0.028)	(0.027)
$PSTOCK_{i,t-1}/(EMP_{i,t-1}/100)$	0.016	−0.002
	(0.007)	(0.008)
$\ln(HHI_{i,t-1})$	−0.016	−0.015
	(0.053)	(0.052)
$\ln(RATING_{i,t-1})$	0.193	0.171
	(0.155)	(0.158)
$\ln(PRE\_R\&D_i)$	0.569***	0.564***
	(0.047)	(0.047)
$NO\_PRE\_R\&D_i$	−0.291	−0.224
	(0.321)	(0.323)
Intercept	−1.834*	−1.659
	(1.008)	(1.026)
Joint significance of industry dummy variables ($\chi^2(10)$)	23.04**	22.71**
Joint significance of time dummy variables ($\chi^2(6)$)	33.32***	33.10***
Log likelihood	−4,389.99	−4,369.11
McFadden R^2	0.41	0.42
Number of observations	2,338	2,338

Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%).
Standard errors are clustered at the firm level (566 clusters).

ables. Blundell et al. (1995, 2002) suggest an entry stock estimator for count data models that has these characteristics. Although we do not have count data, Wooldridge (2002) points out that the Poisson estimator yields consistent estimates whenever the conditional mean is correctly specified even if the dependent variable is not a count. To limit the excessive range of our dependent variable (R&D), we use R&D intensity (in percent) as our dependent variable:

$$RDINT_{it} = (R\&D_{it}/Sales_{it}) \times 100.$$

To control for unobserved heterogeneity, the entry stock estimator uses the presample average of the dependent variable. We calculated the presample average of R&D intensity and entered the variable as $\ln(PRE\_R\&D_i)$ in our specification. If the firm had no R&D in the presample period, a dummy is used to capture the "quasi-missing" value in log of R&D in the presample period, *NO_PRE_R&D* (see Blundell at al., 1995). Note that we observe the presample period for all firms in our sample.

Table A1 shows the regression results using the entry stock estimator. The presample average of R&D intensity is highly significant, which rejects the assumption of no unobserved heterogeneity. The main results found with the tobit model reported in table 2 continue to hold using this alternative estimator. New product uncertainty has a negative impact on current R&D investment and patenting offsets this negative impact. The interaction term of patents and uncertainty is positively significant at the 1% level. Except for the time and industry dummies, our other controls turn out to be insignificant. This owes to the high time-series persistence of variables in levels, such as employment, past sales with new products, and industry concentration, for instance. All effects of these variables seem to be absorbed in the fixed effects.